

DIFFERENTIAL EVOLUTIONARY ALGORITHM FOR ALLOCATION OF SVC IN A POWER SYSTEM

M.M. Farsangi H. Nezamabadi-pour

*Electrical Engineering Department, Shahid Bahonar University, Kerman, Iran
mmaghfoori@mail.uk.ac.ir, nezam@mail.uk.ac.ir*

Abstract- This paper investigates the ability of different strategies of Differential Evolutionary (DE) Algorithm in dealing with optimal placement of Static VAR Compensator (SVC) in a power system. The primary function of an SVC is to improve transmission system voltage, thereby enhancing the maximum power transfer limit. To enhance voltage stability, the planning problem is formulated as a multi-objective optimization problem for maximizing fuzzy performance indices. Two different scenarios are used when DE is applied. The performances of DE with two different scenarios and different strategies are compared in terms of their success rate. To validate the results, Real Genetic Algorithm (RGA) is applied and compared with DE.

Keywords: Differential Evolution, Real Genetic Algorithm, SVC, Multi-Objective Optimization, Fuzzy Performance Indices.

I. INTRODUCTION

In the last decades, efforts have been made to find the ways to assure the security of the system in terms of voltage stability. It is found that flexible AC transmission system (FACTS) devices are good choices to improve the voltage profile in power systems that operate near their steady-state stability limits and may result in voltage instability. Many studies have been carried out on the use of FACTS devices in voltage and angle stability. Taking advantages of the FACTS devices depends greatly on how these devices are placed in the power system, namely on their location and size.

A great deal of work has been carried out to develop analytical and control synthesis tools to detect and avoid voltage instability. In the literature a tool known as modal analysis has been reported, which is based on the determination of critical modes. Modal analysis has been used to locate SVC and other shunt compensators to avoid voltage instability [1].

Over the last decades there has been a growing interest in algorithms inspired from the observation of natural phenomenon. It has been shown by many researches that these algorithms are good alternatives as tools to solve complex computational problems. Due to many good features of Genetic Algorithm (GA), GA has

been widely applied in different applications of power system, such as optimal location of FACTS devices [2]-[11].

Differential evolution (DE) is a stochastic algorithm that performs a multi-directional search by maintaining a population of potential solutions and encourages information exchanges between these solutions. Thus this population can move over hills and across valleys to discover a globally optimal point.

In view of this, this paper considers the problem of planning SVC in a power system to maintain the nodal voltage magnitudes using DE. The problem is formulated as a multi-objective optimization problem for maximizing fuzzy performance indices. The multi-objective optimization problem represents minimizing voltage deviation, the RI^2 losses and cost of installation resulting in maximizing the system VAR margin. The problem is also solved by RGA and the results are compared with the results obtained by DE.

II. DIFFERENTIAL EVOLUTION

DE developed by Rainer Storn and Kenneth Price in 1995 who shown that DE is a powerful tool to optimize real-valued multimodal objective functions as well as unimodal objective function [12]. Unimodal functions are those functions that have a local minimum where for unimodal functions; the convergence rates of the algorithm are more interesting than the final results of optimization (since any approaches can find the optimum solution). Multimodal functions have a few or many local minima and the algorithm must be capable in finding the optimum solution and it should not be trapped in local minima.

DE is similar to a simple genetic algorithm but differs from GA with respect to the mechanism of how mutation, recombination and selections are performed. Suppose an optimization problem is to minimize a fitness function $f(x)$ and $P^G = \{x_1^G, x_2^G, \dots, x_{N_p}^G\}$ is a population of candidate solutions, where N_p is the population size and G is the generation index.

DE generates new parameter vectors by adding the weighted difference between two population vectors to a third vector. If the obtained vector has a lower fitness

function than a predetermined population member, the new generated vector will be replaced; otherwise the old vector is retained. This is the fundamental philosophy behind the DE algorithm where, it can be extended to have different type of DE algorithm. For example an existing vector such as; one or more than one randomly chosen vector or the best performing vector of the current generation; can be perturbed by adding more than one weighted difference vector to it. In some cases, the parameters of the old vector can be mixed with the perturbed vector. DE algorithm is briefly described in the following steps:

Step 1: *Initialization*. The initial vector population is chosen by randomly selection as follows:

$$x_{j,i}^{G=0} = x_{j,\min} + rand_j[0,1] \times (x_{j,\max} - x_{j,\min}) \quad (1)$$

$$i = 1, 2, \dots, N_p; j = 1, 2, \dots, D$$

The initial process can produce N_p D -dimensional individuals of $x_{j,i}^{G=0}$ randomly.

Step 2: *Mutation and Crossover*. By using mutation and crossover, DE creates one child or an offspring (a trial vector $u_{j,i}^{G+1}$) for each parent ($x_{j,i}^G$) as follows:

$$u_{j,i}^{G+1} = x_{j,r3}^G + F \times (x_{j,r1}^G - x_{j,r2}^G) \quad (2)$$

where x_i^G is the i^{th} individual in a set of population $P^G = \{x_1^G, x_2^G, \dots, x_{N_p}^G\}$ at the generation G ; $u_{j,i}^{G+1}$ is a mutated $x_{j,i}^G$ for the next generation; F is the scaling factor which is real and constant value in $[0, 2]$ and controls the amplification of the differential ($x_{j,r1}^G - x_{j,r2}^G$); $x_{j,r1}^G, x_{j,r2}^G$ and $x_{j,r3}^G$ are the j^{th} component of the randomly chosen individuals in the current generation. Equation (2) shows that the vector to be perturbed is randomly chosen ($x_{j,r3}^G$) and that the perturbation consists of one weight difference vector ($x_{j,r1}^G - x_{j,r2}^G$). The graphical view of (2) is shown in Figure 1.

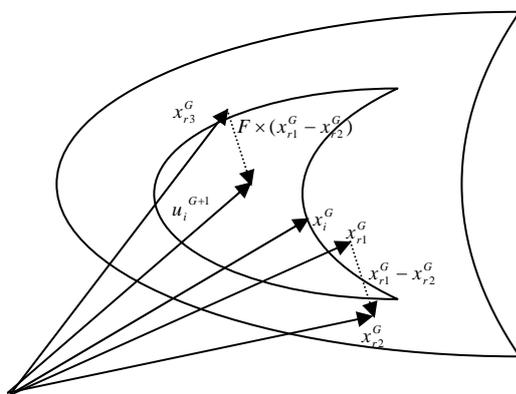


Figure 1. Graphical view of equation (2)

In order to increase the diversity of the individual in the next generation (child), the perturbed individual and the present individual are chosen by a distribution to

progress the crossover operation to yield a vector as follows:

$$u_{j,i}^{G+1} = \begin{cases} u_{j,i}^{G+1} & \text{if } (rand_j[0,1] < CR \text{ or } j = jrand) \\ x_{j,i}^G & \text{otherwise} \end{cases} \quad (3)$$

$$i = 1, 2, \dots, N_p; j = 1, 2, \dots, D$$

In (3) CR is crossover factor which is a constant value $\in [0, 1]$ and assigned by the user. $rand_j$ is the j^{th} evaluation of a uniform random number generator ranging over $[0, 1]$ and $jrand$ is an index randomly chosen from $\{1, 2, \dots, D\}$. When $rand_j[0, 1]$ is less than CR or if $j = jrand$, the child parameter is a linear combination of three randomly chosen vectors; otherwise, the child parameter is its parents. The condition "or $j = jrand$ " ensure that the child vectors will differ from their parents by at least one parameter.

It should be noted that two different types of crossover can be applied on different DE strategies known as exponential and binomodal. In exponential crossover, the crossover is performed on the D variables in one loop until it is within the CR bound. In binomodal crossover, the crossover is performed on each the D variables whenever a randomly picked number between 0 and 1 is within the CR bound.

Step 3: *Replacement*. The parent is replaced by its offspring if the fitness of the offspring is better than its parent. On the other hand, the parent is retained in the next generation if the fitness of the offspring is worse than its parent. The parents for the next generation are selected as follows:

$$x_{j,i}^{G+1} = \begin{cases} u_{j,i}^{G+1} & \text{if } f(u_{j,i}^{G+1}) \leq f(x_{j,i}^G) \\ x_{j,i}^G & \text{otherwise} \end{cases} \quad (4)$$

Based on [12]-[13], the DE mutation is classified into 6 strategies. Both binomodal and exponential crossover can be applied on these strategies resulting to 12 different strategies in DE. The notation "DE/x/y/z" are used to show different strategies where x represents the vector to be perturbed, y is the number of difference vectors considered for perturbation of x and z is the type of crossover denoted as 'bin' or 'exp' for binomodal or exponential respectively.

By the above description, (2) known as the first strategy by the notation of 'DE/rand/1/bin' that specific the vector to be perturbed is randomly chosen and that the perturbation consist of one weight difference vector and binomodal crossover is used. Other strategies are listed below:

Strategy 2: DE/best/1/bin

In this type of DE, the vector to be perturbed is the best performing vector of the current generation and a weighted difference vector is used for the perturbation.

$$u_{j,i}^{G+1} = x_{best}^G + F \times (x_{j,r1}^G - x_{j,r2}^G) \quad (5)$$

where x_{best}^G is the best individual among the population P^G .

Strategy 3: DE/rand-to- best /1/bin

The following perturbation is considered:

$$u_{j,i}^{G+1} = x_{j,r5}^G + F \times (x_{best}^G - x_{j,i}^G) + F \times (x_{j,r1}^G - x_{j,r2}^G) \quad (6)$$

Strategy 4: DE/ rand/2/bin

In this type of DE the vector to be perturbed is randomly chosen and that the perturbation consist of two weight difference vector.

$$u_{j,i}^{G+1} = x_{j,r5}^G + F \times (x_{j,r1}^G - x_{j,r2}^G + x_{j,r3}^G - x_{j,r4}^G) \quad (7)$$

where $x_{j,r4}^G$ and $x_{j,r5}^G$ are the j^{th} component of the randomly chosen individuals in the current generation .

Strategy 5: DE/ best/2/bin

The vector to be perturbed is the best performing vector of the current generation and two weighted difference vectors are used for the perturbation.

$$u_{j,i}^{G+1} = x_{best}^G + F \times (x_{j,r1}^G - x_{j,r2}^G + x_{j,r3}^G - x_{j,r4}^G) \quad (8)$$

Strategy 6: DE/current-to-rand/l/bin

In order to provide a means to enhance the greediness of the scheme, an additional control variable K is introduced. Therefore, the randomly chosen $x_{j,i}^G$ is perturbed by two weighted difference vectors as follows:

$$u_{j,i}^{G+1} = x_{j,i}^G + K \times (x_{j,r3}^G - x_{j,i}^G) + F \times (x_{j,r1}^G - x_{j,r2}^G) \quad (9)$$

where $x_{j,i}^G$ is the j^{th} component of the i^{th} individual

x_i^G ; K is a coefficient of combination.

The exponential crossover can be applied to the above strategies resulting 6 more different strategies as follows:

Strategy 1: DE/rand/l/ exp

$$u_{j,i}^{G+1} = x_{j,r3}^G + F \times (x_{j,r1}^G - x_{j,r2}^G) \quad (10)$$

Strategy 2: DE/Best/1/exp

$$u_{j,i}^{G+1} = x_{best}^G + F \times (x_{j,r1}^G - x_{j,r2}^G) \quad (11)$$

Strategy 3: DE/ rand-to- best /1/ exp

$$u_{j,i}^{G+1} = x_{j,i}^G + F \times (x_{best}^G - x_{j,i}^G) + F \times (x_{j,r1}^G - x_{j,r2}^G) \quad (12)$$

Strategy 4: DE/ rand/2/ exp

$$u_{j,i}^{G+1} = x_{j,r5}^G + F \times (x_{j,r1}^G - x_{j,r2}^G + x_{j,r3}^G - x_{j,r4}^G) \quad (13)$$

Strategy 5: DE/ Best/2/ exp

$$u_{j,i}^{G+1} = x_{best}^G + F \times (x_{j,r1}^G - x_{j,r2}^G + x_{j,r3}^G - x_{j,r4}^G) \quad (14)$$

Strategy 6: DE/current-to-rand/l/exp

$$u_{j,i}^{G+1} = x_{j,i}^G + K \times (x_{j,r3}^G - x_{j,i}^G) + F \times (x_{j,r1}^G - x_{j,r2}^G) \quad (15)$$

As mentioned already, F controls the amplification of the differential vector. DE is more sensitive to changes of F rather than K . In view of this, in this paper as another attempt "a variable scaling factor" is used to alleviate the problem of selecting mutation operator in DE. The rule of updating the scaling factor is based on the 1/5 success rule of the evolution strategies [14] which is defined as follows:

$$F^{t+1} = \begin{cases} c_d \times F^t & \text{if } p_s^t < \frac{1}{5} \\ c_i \times F^t & \text{if } p_s^t > \frac{1}{5} \\ F^t & \text{if } p_s^t = \frac{1}{5} \end{cases} \quad (16)$$

where p_s^t is the frequency of successful mutations measured. The successful mutation is defined when the fitness value of the best individual in the next generation

is better than that of the best individual in the current generation. In fact the rule defined in (16) is a measure to increase the efficiency at the cost of effectiveness or robustness. The factors c_d and c_i are for the adjustment, which should take place in each iteration. They are constant values and based on [14] should take the value 0.82 and 1/0.82, respectively.

III. OPTIMAL PLACING OF SVC

System VAR margin can be evaluated by stressing the system gradually from an initial operating state until the state of critical voltage stability is reached. This can be done by increasing all loads gradually close to the point of voltage collapse. Increasing system VAR margin could be achieved by placing SVC considering the following objective functions:

1) *Active power loss*. The total power loss to be minimized is as follows:

$$P_L = \sum [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] Y_{ij} \cos \phi_{ij} \quad (17)$$

where V_i and δ_i are the magnitude and angle of voltage at bus i , Y_{ij} and ϕ_{ij} are the magnitude and angle of the admittance of the line from bus i to bus j .

2) *Voltage deviation*. To have a good voltage performance, the voltage deviation at each load bus must be made as small as possible. The voltage deviation to be minimized is as follows:

$$f = \max_{k \in \Omega} |V_k - V_{k,ref}| \quad (18)$$

where Ω is the set of all load buses, V_k is the voltage magnitude at load bus k and $V_{k,ref}$ is the nominal or reference voltage at bus k .

3) *Cost function of SVC*. According to [15], the cost function for SVC in terms of (US\$/kVAR) is given by the following equation:

$$C = 0.0003Q^2 - 0.3051Q + 127.38$$

where Q is MVAR size of SVC.

There are a number of approaches to solve the multi-objective optimization problem. Since SVC placement according to the multi-objective functions is difficult with an analytical method, a fuzzy logic technique is proposed in this paper to achieve a trade-off between the objective functions. The multi-objective optimization problem is transformed into a fuzzy inference system (FIS), where each objective function is quantified into a set of fuzzy objectives selected by fuzzy membership functions.

The FIS is composed of fuzzification, inference engine, knowledge or rule base, and defuzzification. The fuzzification process is an interface between the real world parameters and the fuzzy system. It performs a mapping that transfers the input data into linguistic variables and the range of these variables forms the fuzzy sets.

The inference engine uses the rules defined in a rule base and develops fuzzy outputs from the fuzzy inputs. The rule base includes the information given by the expert in the form of linguistic fuzzy rules, or experience gained in the process of experiment [16]-[17]. The defuzzification is a reverse process of the fuzzification. It

maps the fuzzy output variables to the real world, or crisp, variables that can be used in controlling a real world system.

In this paper, the three objective functions, the voltage deviation (f), the power loss (P_L) and installation cost (C) are inputs to the FIS and the output is an index of satisfaction or fitness achieved. The inputs are fuzzified by the membership functions shown in Figures 2-4. The membership function of the output is shown in Figure 5. The inference engine uses the rules defined in Tables 1-3 and develops fuzzy outputs from the fuzzy inputs. The fuzzy output is defuzzified by the Center of Average (COA) method to yield a crisp value for the level of satisfaction or fitness.

Tables 1-3 show the fuzzy rules for solving the problem where, G stands for good, M stands for moderate, B stands for bad, V stands for very and Ex stands for excellent.

Table 1. Fuzzy rules

		Input 1 (f)		
		G	M	B
Input 2 (P_L)	For C(Low)			
	G	Ex	VVG (V2G)	M
	M	VVG	G	B
B	B	VB	VB	

Table 2. Fuzzy rules

		Input 1 (f)		
		G	M	B
Input 2 (P_L)	For C(Med)			
	G	VVG	VG	B
	M	VG	M	VB
B	VB	VB	VVB	

Table 3. Fuzzy rules

		Input 1 (f)		
		G	M	B
Input 2 (P_L)	For C(High)			
	G	VG	G	B
	M	G	B	VB
B	VB	VB	VVB (V2B)	

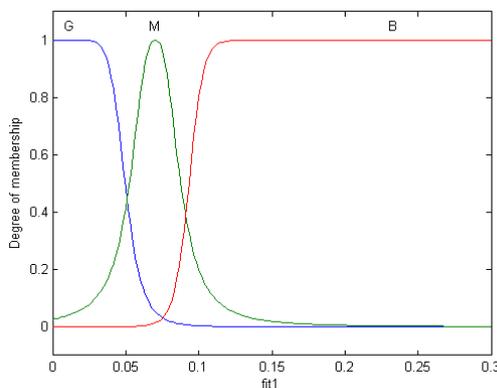


Figure 2. Membership functions for Input 1, voltage deviation (f)

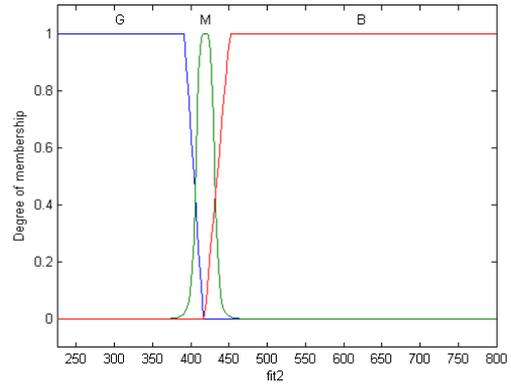


Figure 3. Membership functions for Input 2, active power loss (P_L)

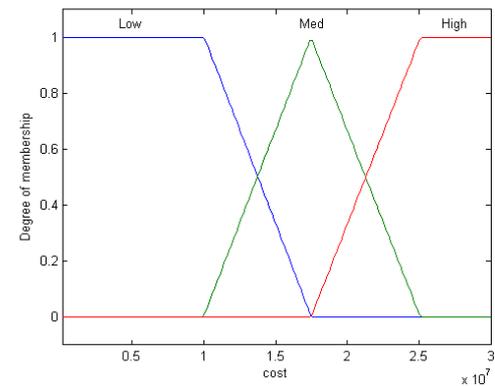


Figure 4. Membership functions for Input 3, cost function (C)

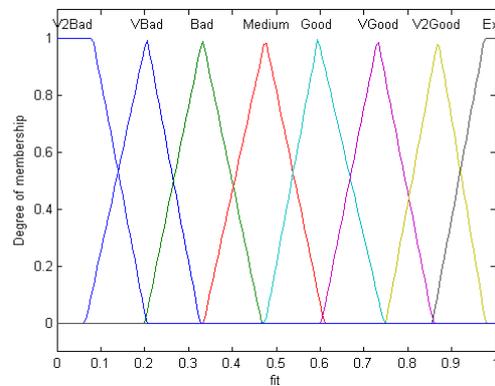


Figure 5. Membership functions for output, the level of satisfaction (fitness)

IV. THE STUDY SYSTEM AND IMPLEMENTATION OF DE AND RGA

The system shown in Figure 6 consists of 16 machines and 68 buses for 5 interconnected areas. The first nine machines, G1 to G9, constitute the simple representation of Area 1. Next four machines G10 to G13, represent Area 2. The last three machines, G14 to G16, are the dynamic equivalents of the three large neighboring areas interconnected to Area 2. The subtransient reactance model for the generators, the first-order simplified model for the excitation systems, and the linear models for the loads and ac network are used. The power system data are obtained from [18].

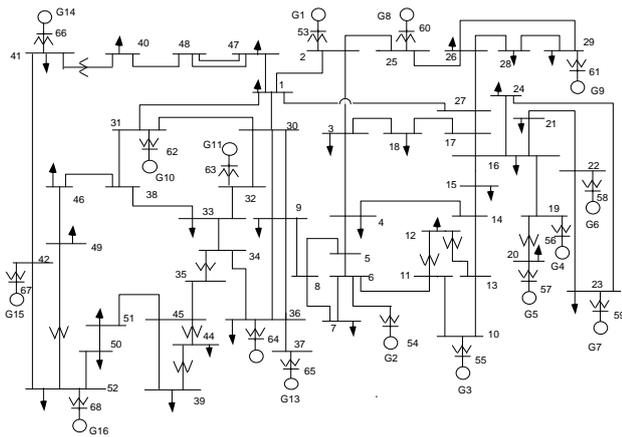


Figure 6. Single line diagram of a 5-area study system

Placing of SVC using DE and RGA starts from an initial load. All loads are increased gradually near to the point of voltage collapse, all at once. Figure 7 shows the profile of the voltage when system is heavily stressed and is reached to the point of collapse.

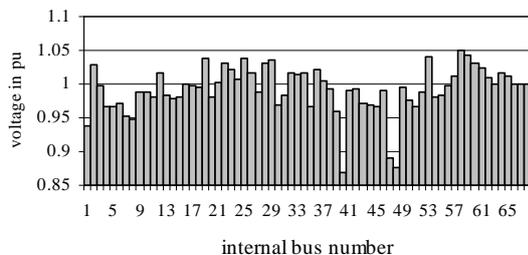


Figure 7. Bus voltage magnitude profile when system is heavily stressed

In the VAR planning with DE two different scenarios are considered:

- *First scenario.* Applying different strategies with exponential and binomodal crossover by considering the scaling factor F constant.
- *Second scenario.* Applying different strategies with exponential and binomodal crossover by considering the scaling factor F as a variable (Equation (16)). The main difference between the first scenario and the second scenario is in the population size (N_p). When F is constant, N_p is set to be 100; but when F is variable, N_p is set to be 5. The reason of decreasing the population to 5 is due to (16) that 1/5 success rule of the evolution strategies adjusts the scaling factor to accelerate searching out the global solution.

IV.A. VAR Planning: First Scenario

In the DE algorithm, N_p individuals are generated randomly. Since optimizations are made on two parameters: its location and size, therefore, each individual is a D -dimensional vector in which $D=2$. The individuals evolve through successive iterations, called generations. During each generation, the individuals are evaluated with some measure of fitness, which is calculated from the FIS.

In this paper, the crossover probability is chosen to be $CR = 0.9$ and the coefficient of combination is selected to be $K = 0.6$. Also, the number of iteration is considered to be 70, which is the stopping criterion. The scaling factor is fixed to be $F = 0.5$. Different strategies in Section 2 are applied. Owing to the randomness of the heuristic algorithms, to locate an SVC by fuzzy DE, suitable buses are selected based on 10 independent runs under different random seeds. With 10 independent runs, all strategies find the optimum solution. The optimum solution shows that an SVC should be placed at bus 1 with 546 MVAR size. Although all strategies find the optimum solution but their convergence characteristic are different. The obtained solutions by different strategies using binomodal and exponential crossover are given in Table 4.

Table 4. The obtained results of different strategies based on 10 independent runs under different random seeds (first scenario)

strategy	binomodal crossover		exponential crossover	
	Finding the optimal solution (bus 1, 546 MVAR)	Finding the sub-optimal solution	Finding the optimal solution (bus 1, 546 MVAR)	Finding the sub-optimal solution
1	100%	-	20%	70%: bus 1 with different MVAR such as 544, 545, 543; 10% bus 41;
2	10%	90%: bus 41, 42, 37, 36	30%	70%: bus 41, 42, 37, 36
3	20%	80%: bus 41, 42, 37, 36	20%	40%: bus 1 with different MVAR such as 544, 543, 541; 40%: bus 41, 37;
4	100%	-	10%	90%: bus 1 with different MVAR such as 543, 541, 527;
5	60%	40%: bus 41, 42, 37, 36	10%	20%: bus 1 with different MVAR such as 5471, 544; 70%: bus 41, 42, 36
6	20%	80%: bus 1 with different MVAR such as 544, 545, 543, 536;	-	90%: bus 1 with different MVAR such as 542, 535, 548; 10%: bus 36

The entries in Table 4 show that the strategies 1 and 4 with binomodal crossover perform better than other strategies, since 100% of the obtained results (10 independent runs) find the optimum solution. Although 100% of the obtained results by strategy 6 with binomodal crossover show that SVC should be placed at bus 1 but different MVAR size are found. These results reveals that the exploration of this strategy is good in finding bus 1 but its exploitation is not good in finding the level of compensation which is 546. Also, the results reveal that DE with binomodal crossover outperforms DE with exponential crossover and the exploitation of DE with exponential crossover is less than DE with binomodal crossover in finding the level of compensation which is 546.

To have a better clarity, the results obtained by DE with different strategies are averaged over independent runs. The average best-so-far of each run are recorded and averaged over 10 independent runs. The convergence characteristics in finding the location and size of an SVC for different strategies with both crossovers are given in Figures 8-9. These figures illustrate that for the current problem, three strategies 1, 4 and 6 have better features in finding optimal solution compared to other strategies. Also, comparing of Figures 8 and 9 shows that DE with binomodal crossover can performs better than DE with exponential crossover.

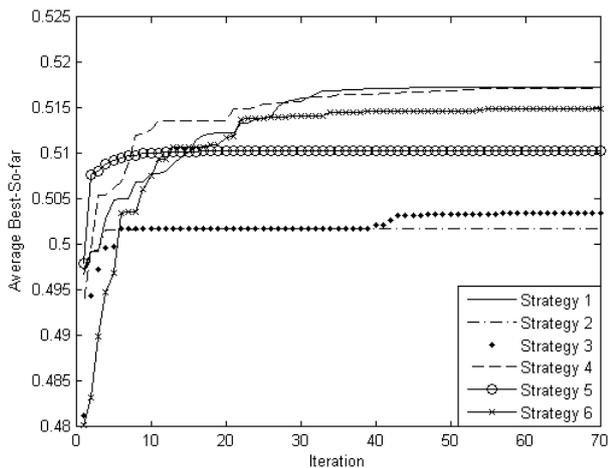


Figure 8. Convergence characteristics of DE with binomodal crossover on the average best-so-far in finding the solution, placement of SVC at bus 1

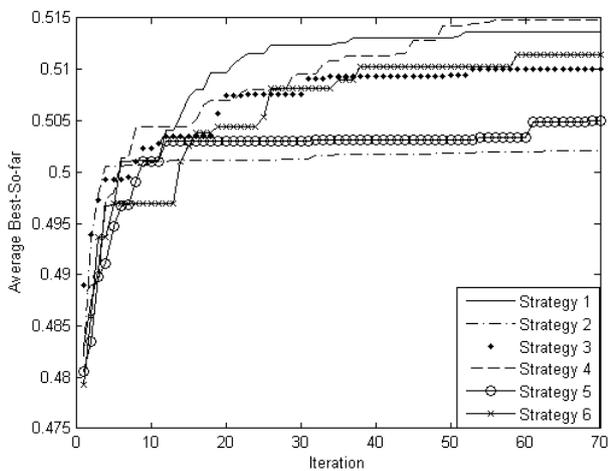


Figure 9. Convergence characteristics of DE with exponential crossover on the average best-so-far in finding the solution, placement of SVC at bus 1

Since DE is a real-valued optimization algorithm, for fair comparison, the Real version of GA (RGA) is used to validate the results obtained by the DE. As in the DE, the number of population and iterations is considered to be 100 and 70, respectively.

In RGA, the chromosomes evolve through successive iterations, called generations. During each generation, the chromosomes are evaluated with some measure of fitness, which is calculated from the FIS.

Moving to a new generation is done from the results

obtained for the old generation. A biased roulette wheel is created from the obtained values of the objective function of the current population. To create the next generation, new chromosomes, called offspring, are formed using a crossover operator and a mutation operator. In RGA, linear crossover and Gaussian mutation are used with the crossover probability $p_c = 0.9$ and the mutation probability is selected to be $p_m = 0.05$.

As in the case of DE, suitable bus is selected based on 10 independent runs under different random seeds. 20% of the obtained results reveal that the SVC should be placed at bus 1 with 546 and 504 MVAR size and 70% of results show that the SVC should be placed at bus 47 with different MVAR size.

The best-so-far of each run is recorded and averaged over 10 independent runs. Convergence characteristics in finding the location and size of an SVC is given in Figure 10. This figure shows that DE has a better feature to find the optimal solution.

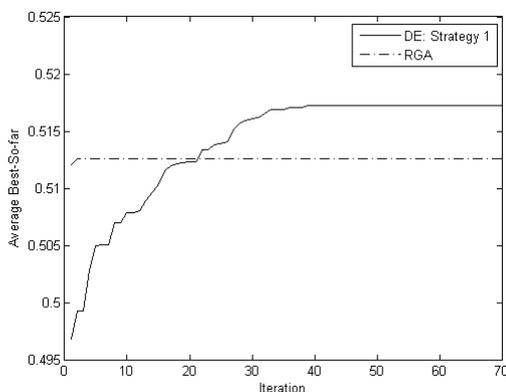


Figure 10. Convergence characteristics of strategy 1 with binomodal crossover and RGA on the average best-so-far in finding the optimum solution, placement of SVC at bus 1 with 546 MVAR

Now an SVC with the obtained MVAR size (546) will be placed at bus 1. The profile of the voltage is shown in Figure 11. This figure shows that the voltage profile has been improved perfectly. The maximum voltage in Figure 11 is 1.05 and the minimum voltage is 0.95 at bus 8.

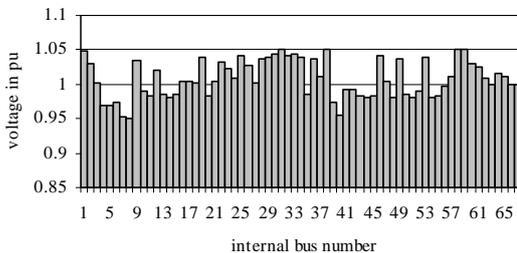


Figure 11. Bus voltage magnitude profile of the stressed system after placing 546 MVAR SVC at bus 1

IV.B. VAR Planning: Second Scenario

As mentioned before, the population size N_p is considered to be 5. The crossover probability is chosen to be $CR = 0.9$. The initial value of the scaling factor is set to 1.2 and it will be adjusted by the algorithm based on

(16). c_d is set to be 0.82 and c_i is chosen to be 1/0.82 [14]. Once again, suitable buses are selected based on 10 independent runs under different random seeds. The obtained solutions by different strategies using binomodal and exponential crossover are listed in Table 5.

Table 5. The obtained results of different strategies based on 10 independent runs under different random seeds (second scenario)

Strategy	binomodal crossover		exponential crossover	
	Finding the optimal solution (bus 1, 546 MVAR)	Finding the sub-optimal solution	Finding the optimal solution (bus 1, 546 MVAR)	Finding the sub-optimal solution
1	50%	50% : bus 47, 42	-	20%: bus 1 with different MVAR such as 527, 507; 80%: bus 47, 30, 42;
2	30%	70%: different buses: 47, 41, 42, 48	-	20%: bus 1 with different MVAR such as 527, 507; 80%: bus 47, 30, 42;
3	30%	70%: different buses: 36, 37, 42, 47	-	30%: bus 1 with different MVAR such as 527, 507; 70%: bus 47, 42;
4	40%	50%: different buses: 36, 37, 42, 47; 10%: bus 1, 542	-	50%: bus 1 with different MVAR such as 527, 507, 548; 50%: bus 47, 42, 37;
5	10%	90%: bus 36, 37, 42, 47	-	40%: bus 1 with different MVAR such as 530, 527, 561; 60%: bus 47, 42, 37;
6	10%	50%: bus 1 with different MVAR such as 541, 515, 543; 40%: bus 47, 41, 42,	-	60%: bus 1 with different MVAR such as 5708, 536, 530; 40%: bus 41, 36, 37;

Once again, three strategies 1, 4 and 6 have better exploration in finding optimal solution compared to other strategies but the exploitation of strategies 1 and 4 are better than others. Also, DE with exponential crossover with 5 populations performing poor in finding the optimum solution (bus 1 with 546 MVAR).

As mentioned in section 2, the rule defined in (16) is a measure to increase the effectiveness or robustness of the algorithm. To show this, the population of the first strategy of the first scenario (when F is a constant parameter) is decreased to 5 and the results obtained are compared with the first strategy of the second scenario (when F is a variable parameter). In the first strategy of the first scenario, when the population is decreased to 5, only 20% of the obtained results find the optimum solution, while 50% of the obtained results by the first strategy of the second scenario find the optimum solution which shows that the robustness of the algorithm has improved.

V. CONCLUSIONS

The aim of this paper is to investigate the ability of DE algorithm in multi-objective VAR planning by SVC which is based on the reduction of the system losses, reduction of voltage deviations and reduction of installation cost. Different strategies in DE are applied with two different scenarios, the first one with constant scale factor and the second one with variable scale factor. Their performances are compared in terms of their success rate. Three strategies 1, 4 and 6 with binomodal crossover perform better than other strategies. The exploration of these strategies is better than other strategies but the exploitation of the strategy 1 and 4 is better than strategy 6 in finding the optimum solution. Also, those strategies of DE with binomodal crossover give better solution than those strategies with exponential crossover. To validate the results carried out by DE, RGA is applied where DE has a better convergence rate.

Although the strategies 1 and 4 of the first scenario with 100 population are performing better than the second scenario with 5 population, but the point is that with the small population size of DE for variable scaling factor, the algorithm leads us to the optimal solution with a reasonable robustness. Also, small population results in less execution time. The execution time for 10 independent runs of the first scenario is much higher than that for 10 independent runs of the second scenario (about twenty times). The results show that DE with 5 populations has a great potential in solving the power system problems. It could be very useful for those on line problems due to quick response in finding optimal solution.

REFERENCES

- [1] S. Ebrahimi, M.M. Farsangi, H. Nezamabadi-Pour and K.Y. Lee, "Optimal Allocation of STATIC VAR Compensators using Modal Analysis, Simulated Annealing and Tabu Search," *Proc. 2006 IFAC Symposium on Power Plants and Power Systems*, Calgary, Canada, 2006.
- [2] M.M. Farsangi, H. Nezamabadi-Pour and K.Y. Lee, "Multi-Objective VAR Planning with SVC for a Large Power System Using PSO and GA," *Proc. 2006 IEEE PES Power Systems Conference and Exposition (PSCE)*, Atlanta, USA, 2006.
- [3] P. Paterni, S. Vitet, M. Bena and A. Yokoyama, "Optimal location of Phase Shifters in the French Network by Genetic Algorithm," *IEEE Trans. Power Systems*, 14 (1), pp. 37-42, 1999.
- [4] H.C. Leung and T.S. Chung, "Optimal Placement of FACTS Controller in Power System by a Genetic Based Algorithm," *Proc. 1999 IEEE Power Electronics and Drive Systems Conference*, Vol. 2, pp.833-836, 1999.
- [5] S. Gerbex, R. Cherkaoui and A.J. Germond, "Optimal Location of Multi-Type FACTS Devices in a Power System by Means of Genetic Algorithms," *IEEE Trans. Power Syst.*, 16 (3), pp. 537-544, 2001.
- [6] F. Wang and G.B. Shrestha, "Allocation of TCSC Devices to Optimize Total Transmission Capacity in a

Competitive Power Market," *Proc. 2001 IEEE Winter Meeting*, 2 (2), pp. 587-593, 2001.

[7] E.E. El-Araby, N. Yorino and H. Sasaki, "A Comprehensive Approach for FACTS Devices Optimal Allocation to Mitigate Voltage Collapse," *Proc. 2002 IEEE Transmission and Distribution Conference*, Vol. 1, pp.62-67, 2002.

[8] L.J Cai, I. Erlich and G. Stamsis, "Optimal Choice and Allocation of FACTS Devices in Deregulated Electricity Market Using Genetic Algorithms," *Proc. 2004 IEEE PES General Meeting*, pp. 201-207, 2004.

[9] N.P. Padhy, M.A. Abdel-Moamen and B.J. Praveen Kumar, "Optimal Location and Initial Parameter Settings of Multiple TCSCs for Reactive Power Planning Using Genetic Algorithms," *Proc. 2004 IEEE PES General Meeting*, Vol. 1, pp. 1110-1114, 2004.

[10]L. Ippolito and P. Siano, "Selection of Optimal Number and Location of Thyristor-Controlled Phase Shifters Using Genetic Based Algorithms," *IEE Proc. Gener., Transm. Distrib.*, 151 (5), pp. 630-637, 2004.

[11]K.Y. Lee, X. Bai, and Y.M. Park, "Optimization Method for Reactive Power Planning Using a Genetic Algorithm," *IEEE Trans. Power Systems*, 10 (4), pp. 1843-1850, 1995.

[12]K. Price and R. Storn, "Differential Evolution", <http://www.ICSI.Berkeley.edu/~storn/code.html> .

[13] D. Corn, M. Dorigo and F. Glover "New Ideas in Optimization", McGraw-Hill, 1999.

[14]T. Back, F. Hoffmeister, and H.P. Schwefel, "A Survey of Evolution Strategies," *Proc. Fourth Int. Conf. Genet., Algor.*, pp. 2-9, 1991.

[15]C.S. Chang, J.S. Huang, "Optimal Multiobjective SVC Planning for Voltage Stability Enhancement," *IEE Proc.-Gener. Distrib.*, 145 (2), pp. 203-208, March 1998.

[16]P. Ramaswamy, R.M. Edwards, and K.Y. Lee, "An Automatic Tuning Method of a Fuzzy Logic Controller for Nuclear Reactors," *IEEE Transactions on Nuclear Science*, 40 (4), pp. 1253-1262, 1993.

[17]Y.M. Park, U.C. Moon, and K.Y. Lee, "A Self-Organizing Fuzzy Logic Controller for Dynamic Systems Using Fuzzy Auto-Regressive Moving Average (FARMA) Model," *IEEE Transactions on Fuzzy Systems*, 3 (1), pp. 75-82, 1995.

[18]J.H. Chow, "Power System Toolbox: A Set of Coordinated M-Files for Use with MATLAB," Cherry Tree Scientific Software, 1997.

BIOGRAPHIES



Malihe Maghfouri Farsangi received her B.S. degree in Electrical Engineering from Ferdousi University, Iran in 1995, and Ph.D. degree in Electrical Engineering from Brunel Institute of Power Systems, Brunel University, UK in 2003. Since 2003, she has been with Kerman

University, Kerman, Iran, where she is currently an Assistant Professor of Electrical Engineering. Her research interests include power system control and stability and computational intelligence.



Hossein Nezamabadi-pour received his B.S. degree in Electrical Engineering from Kerman University in 1998, and his M.Sc. and Ph.D. degree in Electrical Engineering from Tarbait Moderres University, Iran, in 2000 and 2004, respectively. Since 2004, he has been with Kerman

University, Kerman, Iran, where he is currently an Assistant Professor of Electrical Engineering. His interests include pattern recognition, soft computing, evolutionary computation and image processing.